Neural Networks and SDR Modulation schemes for wireless mobile nodes: a synergic approach

Francesca Guerriero, Valeria Loscrì, Pasquale Pace, Rosario Surace

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Abstract—In this paper, we envisage the possibility to exploit, in a synergic way, the Software Defined Radio (SDR) capability and the mobility support for wireless devices to dynamically compute the most suitable modulation scheme and the best position in order to improve both the coverage and connectivity in a specific area. The combined approach is based on a *Neural/Genetic* technique and wireless nodes are able to self-organize in a totally distributed way by using only local information. The extreme adaptability to the network conditions and application level constraints makes the proposed approach well suited for different communication scenarios such as standard monitoring or disaster recovery. The system performance has been evaluated by dealing a suite of simulation tests to show as the controlled mobility paradigm, coupled with the intrinsic re-configuring SDR capabilities of such wireless devices, allows to increase the network performances both in terms of coverage and connectivity by dynamically adapting the modulation schemes to the specific communication scenario.

Index Terms—Self-Organizing Networks, SDR, Controlled Mobility, Neural Network, Genetic Algorithm.

1 Introduction

Very recently, the idea of designing new communication devices, capable to adapt their operation roles in a self-organized fashion to rapidly face the changes within the working environment, has gained a very high attention from the wireless network research community [1], [2]; similarly, the availability of novel general purpose and powerful hardware platforms able to be dynamically reconfigured via software, has paved the way for new research directions in which it is possible to deploy extremely challenging communication scenarios. [3], [4].

Being inspired by this novel communication trend and, taking into account the unique features offered by the recent *Software Defined Radio (SDR)* paradigm, we considered the design of a self-adapting deployment strategy for a communication network in which several wireless devices, scattered all around in a specific area, can carry out a common task according to specific network requirements in terms of coverage or connectivity. In this context, aiming at handling very unlike communication scenarios, we firmly believe that, the SDR capabilities of future wireless devices can be effectively improved by coupling them with the potential offered by a wise *controlled mobility* strategy to exploit different reconfiguration and self-adaptation levels.

By following this first intuition, the paper proposes a distributed *Neural/Genetic* algorithm to compute the final nodes positions and the more performing modulation schemes for each transmitter/receiver pair in order to guarantee an agreed QoS level. In particular, by considering a generic SDR architecture [5], the major advantages consisting into the ability of automatically selecting the more suitable modulation scheme to be used for an unknown received signal, can be effectively achieved. Thus, as a channel capacity varies, modulation scheme switching enables the baud rate to be increased or decreased in order to maximize the channel capacity usage. In addition, as demonstrated in our preliminary studies [7], SDR capabilities supported by a wireless node, coupled with the controlled mobility functionality, can improve the overall system performances in terms of connectivity. Therefore, such mobile SDR nodes turn out to be very useful for communication scenarios in which, the requirements on constrained QoS connectivity, are more stringent respect to the ones on the maximum coverage.

An example of such communication scenario could be the case of a *disaster area* where the communication between the survivors and the rescue teams has to guarantee a good quality level [6]; on the other side, a communication scenario mostly related to applications such as *pollution monitoring* or *fire detection* only need a high coverage degree that can be achieved by taking advantages just from the mobility of the nodes

Francesca Guerriero, is with the Mechanical, Energy and Management Engineering Department (DIMEG), University of Calabria, Cosenza, Italy. Email: francesca.guerriero@unical.it

Valeria Loscrí is with FUN Team at Inria Lille - Nord Europe. Email: valeria.loscri@inria.fr

Pasquale Pace and Rosario Surace are with the Computer Science, Modelling, Electronics and Systems Engineering Department (DIMES), University of Calabria, Cosenza, Italy. Email:{ppace,rsurace}@dimes.unical.it

without using the SDR capabilities.

In summary, we made the following contributions in this paper:

- we discussed the potential of mobile SDR communication devices in terms of both dynamical re-configuration and operation flexibility;
- we shown how the SDR capabilities supported by the wireless node, coupled with the controlled mobility functionality driven by a distributed Neural/Genetic, can improve the system performances in terms of connectivity by also guaranteeing an agreed QoS level;
- we designed and validated an optimization model in order to prove, in a mathematical way and on a very simple communication scenario, the goodness of the proposed Neural/Genetic algorithm before to conduct a more complex and intensive simulation analysis;
- we validated, throughout a self developed simulator based on a widely used open source framework for evolutionary design, the proposed strategy in different communication scenarios by varying both the amount of mobile and SDR nodes to measure the impact of a larger number of Mobile/SDR nodes on the overall system performances.

The rest of the paper is organized as follows: Section 2 presents few recent research works on deployment techniques for wireless nodes and adaptive modulation schemes implemented via SDR. Section 3 describes which technologies and specific features the devices involved in the proposed communication scenario should support, by highlighting hardware and software capabilities. Section 4 presents the Neural/Genetic algorithm able to compute the best positioning for the wireless nodes to satisfy the constraints imposed by the specific communication scenario. Section 5 presents the proposed optimization model to describe and validate the system behaviour from a mathematical point of view. Section 6 discusses the obtained results and the goodness of the proposed approach in terms of extreme adaptability in different communication scenarios, whilst the conclusions and future research directions have been drawn in Section 7.

2 Related Works

In this work we envision two main topics: 1) deployment techniques for different communication scenarios and 2) adaptive modulation schemes for nodes equipped with SDR capabilities. From the synergical combination and integration of *Neural* and *Genetic* approaches, we designed an algorithm able to compute the best position and the most suitable modulation scheme for each node involved into the communication path. According to these remarks, we first recall few contributions on positioning techniques for wireless nodes that have attracted much research attention becoming increasingly important in recent years. In [22] the authors try to outline the main criteria that should be considered while deploying wireless nodes in a sensor field. Fundamentally, they give an overview of multi-objective approaches by outlining the main assumptions and the formulation of this challenging problem. In [23], the author argues that the communication holes in wireless networks is the main problem causing inefficiency; thus it needs to be effectively addressed. More precisely, sensor nodes can be moved from an initial "unbalanced" state to a "balanced" state, where the number of communications holes is minimized. In [24] the authors distinguish placement approaches by considering deterministic and non-deterministic techniques. Often, non-deterministic placements are also named as random placements, while deterministic placements are referred as controlled placements and the authors refer to the two approaches by keeping this kind of assumption. The choice of how to deploy the sensors in a field, is often affected by the specific application, the type of sensors, the environment in which the sensors operate, etc. The possibility to control a node deployment can be extremely advantageous in terms of operational costs. Based on this last consideration, we figure out to equip wireless nodes with motion capabilities in order to make them able to move towards specific and more convenient locations by obtaining a dynamic changing of the topology/deployment. In this way, it could be add more control to the network and consequently outperform the operational costs. Generally, the survey we cited above, group the deployment techniques based on some specific network parameters such as coverage, lifetime, connectivity, or two or more of them together, but do neither consider at all the possibility for the nodes to autonomously move towards a specific position nor to adapt the modulation scheme to some specific requirements. In this work we consider the possibility to "change" the modulation scheme in order to guarantee a certain Bit Error Rate (BER) level, and in case this constraint can be satisfied by selecting more than one scheme, we select the most efficient in terms of energy consumption. For this reason, the contributions that compare modulation schemes selection to increase coverage and/or connectivity are considered also as related work. In [7] we present the preliminary idea to opportunistically select the more appropriate modulation scheme in order to achieve a certain degree of coverage and connectivity. The added value in respect of [7] is first of all in terms of a general benchmark definition, computed through the formulation of the combined coverage and connectivity problems as a multi-objective optimization problem. Moreover, we provide more details in terms of results by validating the algorithm we propose in several communication scenarios. Starting from 2007, Stuckmann and Zim-

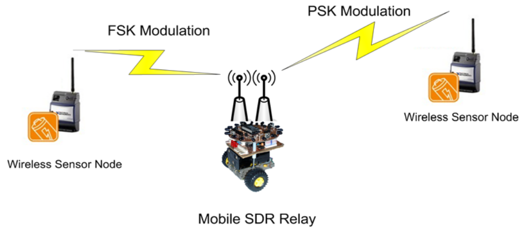


Fig. 1. Mobile relay devices supporting SDR capabilities

mermann [25] envisaged SDR technology as one of the four main objectives, to develop European technologies for systems beyond 3G. Specifically, the spectrum and resource management to make efficient the use of existing spectrum resources can be realized in an feasible and effective way through the application of the SDR concept. The importance of this kind of technology is shown in [26], where the authors propose to optimize the throughput of the network, working in different channel conditions, by considering an automatic modulation switching method to reconfigure the transceivers of SDR systems. We propose a similar approach but with a different purpose, namely a multi-objective algorithm where the goals are both the coverage and the connectivity, in addition the technique is also energy-aware because, where more solutions are feasible, the best one in terms of energy-consumption is selected. Finally, in [27], the authors analyse different modulation techniques in combination with SDR. In practice, they outline again the importance of this kind of technology for the future mobile communication systems.

3 Smart mobile devices supporting SDR

New powerful devices supporting SDR capabilities will be used in the next future to form a self-evolving wireless network in which several goals such as coverage increase, high data rate and connectivity will be achieved in diverse communication scenarios. For this reason, with the aim of considering a quite modern communication context, we studied the case in which both simple mobile or fixed sensor nodes equipped with a wireless IEEE 802.15.4/ZigBee compliant RF transceiver, are considered. Furthermore, we also took into account the presence of more complex mobile devices, with a high processing capability, able to dynamically change the modulation scheme between different transmitter/receiver pairs by using the SDR support as shown in Figure 1. In addition, we assume that these wireless devices are equipped with a GPS module coupled with a software application for position coordinates exchange to perform a specific positioning strategy as detailed in the next section.

By exploiting the new features of programmable SDR architectures, a flexible implementation of several modulation schemes (*i.e.* MFSK, MPSK, MQAM) can be realized in a simple and effective way. This flexibility turns into a great adaptivity to optimize different network performance indexes such as throughput, coverage and degree of connectivity of a wireless networks operating under varying channel conditions. In this context, the devices equipped with SDR functionalities can easily work as relay nodes in a multi-hop communication scenario by dynamically adapting different modulation schemes between the receiving and transmitting phases with the aim of optimizing network performances such as BER (Bit Error Rate), energy consumption and overall coverage.

It is well known that channel modulation has a relevant impact on the quality of the wireless link measured in terms of BER and on software/hardware complexity; furthermore, digital modulation/demodulation techniques need specific channel waveform coherence, coding/decoding and spreading/despreading of the radio spectrum [8]. Since the bit error probability is a function of the channel modulation, a radio channel with better quality has to be assigned to a larger number of bits and a higher order modulation, whereas a channel with poorer quality has to be assigned fewer bits or even no bit when the channel quality is too bad. For example, by working with three main digital modulation schemes (*i.e.* MFSK, MPSK, MQAM) having different modulation orders (M=$2,4,8,16$), it is possible to select and to use the most suitable combination by implementing it on-the-fly throughout SDR techniques. Moreover, to guarantee a certain BER value, the modulation schemes could be dynamically changed according to the channel quality experienced by the nodes and the distance variation between nodes due to the mobility.

In the last few years, the SDR paradigm is becoming more attractive and feasible thanks to the development of open-source software tool-kit such as GNU radio [10] and hardware devices such as Universal Software Radio Peripheral (USRP) [11]; therefore, several modulation/demodulation software blocks can be developed within the generic SDR architecture [9] for both transmitter and receiver (see Figure 2) allowing the design of new and more powerful devices well suited to support the dynamic modulation changing and adaptation strategies proposed in this work [4], [12].

In particular, it is worth to note that, with reference to the complexity of such software/hardware architecture, the Hybrid Radio Architecture (HYRA) proposed in [12] addresses the implementation of SDRs in the context of embedded systems by using reconfigurable hardware platforms with minimal additional resources.

Regarding the mobility features implementation,

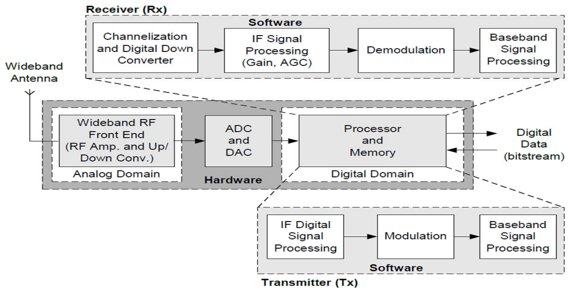


Fig. 2. SDR architecture for Relay Node [9].

TABLE 1
Costs to implement SDR devices.

Mobility Support	SDR Support
Wheels + servo motors + Arduino	USRP B200
250$	800$

we would like to remark that this feature can be implemented by equipping a network device with two or four wheels and a servo motor controlled by Arduino-based modules. The estimated cost of implementing controlled mobility and reconfiguration capability in such platforms is reported in the Table 1. Even if this kind of software/hardware architectures seem quite expensive, the fast technological advancements will favour the reduction of estimated costs; thus, it is plausible that the mentioned embedded architectures will shortly be available at a much lower cost.

4 Neural Network and Genetic Algorithm

The proposed work aims at computing, in a fully distributed fashion, the best positions for wireless devices belonging to a network placed in a given area, in order to satisfy some specific network requirements. In particular the algorithmic scheme, to be performed by each node, consists of a neural network used to control and compute the next movement within the network area, and a genetic algorithm to perform a new solution that better fits with the desired objective function. Since the computation of the new nodes' position can be only based on local information, both the components of the proposed scheme are performed in a distributed way: a node executes the neural algorithm by knowing the positions of its neighborhood and the genetic algorithm manages its own genes without using global information.

Specifically, the two objectives considered in this work, namely, the coverage area and the number of sensor devices having a path toward a sink with a certain quality of service, are in contrast one to each other. Therefore we designed a wise strategy, based on the approach presented in [13], able to take into account both the requirements in a dynamic and reconfigurable fashion.

4.1 The Neural Network

The neural network determines the movements of each wireless node; it is fully connected, recurrent and time-discrete. The neural network consists in input, output and hidden neurons. Inputs are subdivided as follows:

- 4 inputs to detect overlapping of sensing zone with neighborhood' sensing zone (1 for each direction);
- 4 inputs to detect missing of sink connection (1 for each direction);
- 1 to detect nodes in the same position.

The output is the new position. Each neuron "actives" a real-valued function and a time-varying real-valued connection with every other neuron of the network to map input (n-dim) in output (m-dim). We indicate with out_j the output of neuron j towards all other neurons of the network. The output of neuron j is computed as shown in Equation (1).

$$out_j(k) = F\left(\sum_{i \in N} w_{ij} \cdot out_i(k-1) + b_j\right) \qquad (1)$$

where N is the set of neurons, w_{ij} is the weight of the connection between neuron i and neuron j and b_j is the bias of neuron j. Weights can produce both excitatory or inhibitory effect. The activation function F is the following linear threshold function:

$$F(x) = \begin{cases} -1.0 & \text{if} \quad x \leq -1.0 \\ x & \text{if} \ -1.0 < x < 1.0 \\ 1.0 & \text{if} \quad x \geq 1.0 \end{cases} \qquad (2)$$

For each node the output of the neural network is given from the two output neurons and it is consists of two real numbers that vary in the range $[1, -1]$, as it is clear from (2) and Fig. 3. Based on these two values, the node chooses the action to do. Assuming a square field of $n \times n$ cells, the node can move in one of the four allowed directions or remain in the current cell.

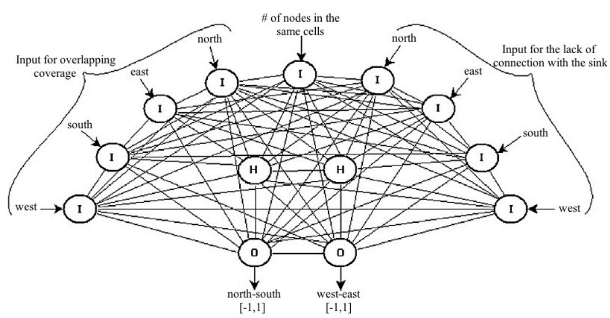


Fig. 3. Neural network architecture of one node

4.2 The Genetic Algorithm

A conventional and real-value Genetic Algorithm (GA) is used in the training phase of the Neural Algorithm. The genes are associated with the connections weights between each couples of neurons and the bias of each neuron. Through the typical operators of genetic approaches (*i.e.* crossover, mutation and selection), different weights to the neurons in the next generations will be assigned. Of course, the chromosome selected for the next generations is the one which has the best value of the fitness function. In our work, we consider a bi-objective functions in order to: 1) maximize the coverage; 2) maximize the number of nodes connected to the sink either in a direct fashion or through a multi-hop path. The fitness function can be written as follows:

$$fitness = \alpha * Coverage + \beta * QoS_{connectivity} \tag{3}$$

where

$$Coverage = \frac{covered\_area}{whole\_area} \tag{4}$$

and

$$QoS_{connectivity} = \frac{\#nodes\_connected\_to\_the\_sink}{\#total\_nodes} \tag{5}$$

where α and β are weights that take into account the priority of the objective to be reached.

The term $\#nodes\_connected\_to\_the\_sink$ represents the number of nodes "connected" to the sink, namely nodes that are able to reach the sink directly or for which exists a multi-hop path [14] throughout links that are able to deliver data by guaranteeing a certain value of BER given as an input constraint. To the follow we show the pseudo-code of the Neural/Genetic Algorithm.

Algorithm 1 Neural/Genetic Algorithm

```
Random Deployment of Wireless Devices;
for all generation i do
    for all chromosome j do
        for all node n do
            while time < time_MAX do
                Compute the new position of n through the neural algorithm;
                Compute the modulations that n must use to reach either the
                other nodes and the sink by guaranteeing a specific QoS; (see
                Section 4.4);
                Among all the modulations satisfying the QoS choose those
                that require less energy (this only a possible choice, we could
                also consider the modulations that maximize the throughput,
                etc.) (see Section 4.5);
            end while
        end for
        Compute chromosome fitness j;
    end for
    Consider the chromosome with the highest fitness value, apply genetic
    operators and then consider it as input for the next generation i+1;
end for
```

4.3 Supported Connectivities and Communication Complexity

As already explained, each node has a set of possible modulations that can be "used" for data transmission by guaranteeing different connectivity levels. In this work, we figure out two different types of connectivities:

- $Basic_{Connectivity}$: according to a specific propagation model, it is possible to compute the maximum distance at which a node n_1 is able to transmit, that is the transmitting radius. If a node n_2 is inside the area delimited by the circle with radius equal to the transmitting radius of the node n_1, then n_1 and n_2 are connected. In this work we consider the propagation model as defined in [15]:

$$PL_{generic} = \left(\frac{4\pi d_0}{\lambda}\right)^2 \cdot \left(\frac{d}{d_0}\right)^\gamma + \chi \tag{6}$$

  where d is the distance between the Tx and the Rx, γ is the path loss exponent, λ is the wavelength, χ is the shadowing effect value (neglectable) and d_0 is the critical distance.
- $QoS_{Connectivity}$: each node n has a neighborhood. For every neighbor, the node n computes the BER value on the specific link by considering the different available modulations. The node n excludes all the modulations that do not respect the BER required as constraint in input. In practice, in this way the node n has a set of neighbors and every link from n to the neighbor meets the QoS constraint in terms of BER computed according to the formulas shown in the next subsection.

For each iteration of the algorithm and for every node, both the $Basic_{Connectivity}$ and the $QoS_{Connectivity}$ are computed.

Since the proposed algorithm is based on local communication, a node only needs to know the position of its neighboring nodes to make a movement. According to [13], after each nodes movement, an update on the nodes position is broadcasted through a constant size message containing the node identifier (*Id*) and the node position (*x*,*y*), therefore the message size is in $O(1)$. As a consequence, considering a constant value for the number of time steps given as an input parameter, nodes will update their positions and broadcast their new information at each time step; this leads to a linear message sending complexity of $O(n)$ where n is the number of nodes within the network.

4.4 BER Computation

In order to compute the BER value related to each specific modulation scheme, we used the following relations coming from an asymptotic approximation [21]:

$$BER_{M-FSK} \approx 2^{k-2} \cdot erfc\left(\sqrt{\frac{k}{2}\frac{E_b}{N_0}}\right) \quad (7)$$

$$BER_{M-PSK} \approx \frac{1}{k} \cdot erfc\left(\sqrt{k\frac{E_b}{N_0}\sin^2\left(\frac{\pi}{M}\right)}\right) \quad (8)$$

$$BER_{M-QAM} \approx 2\frac{\sqrt{M}-1}{\sqrt{M}k} \cdot erfc\left(\sqrt{\frac{3k}{2(M-1)}\frac{E_b}{N_0}}\right) \quad (9)$$

$$BER_{8-QAM} \approx \frac{5}{12} \cdot erfc\left(\sqrt{\frac{1}{2}\frac{E_b}{N_0}}\right) \quad (10)$$

In particular, the BER computation for the QAM modulation needs the use of two different formula according to the particular shape: formula (9) for squared modulations and formula (10) for non squared such as 8-QAM.

4.5 Transmitted Energy Computation

In order to save energy for the transmission always guaranteeing the required QoS level, it is necessary to choose the less power hungry modulation scheme within the set of the the most common modulation schemes available in real devices. To this aim, the energy spent per information bit $[J]$ can be computed as follows [18]:

- For both MQAM and MPSK, by considering a signal bandwidth equal to $B[Hz]$ and, by assuming a sample time $T_s \approx 1/B$ [19], we can write:

$$E_{infBit} \approx \frac{(1+\delta) \cdot SNR \cdot N_0 \cdot N_f \cdot G_d}{R} + \frac{P_c}{R \cdot B} + \frac{P_{tr} \cdot T_{tr}}{L} \quad (11)$$

  where $\delta = \xi/\eta - 1$, ξ is the peak-to-average power ratio (PAPR) of the signal depending on the specific modulation, constellation size and shape[1] whereas η is the efficiency of PA drain chosen equal to 0.35 as typical value of class A power amplifiers [19]. P_{tr} and T_{tr} are the consumed power and the time spent in *transient* mode respectively whilst L is the total number of information bits. The $SNR = \frac{P_{rx} \cdot T_s}{N_0 \cdot N_f}$, where P_{rx} is the received signal power, $N_0/2$ is the power spectral density of the noise and N_f is the receiver noise figure. Moreover, by assuming a general path-loss model, the value of G_d can be computed according to the Equation (6) and it is equal to $G_d = (\frac{4\pi d_0}{\lambda})^2 \cdot (\frac{d}{d_0})^\gamma$. Finally, the term P_c represents the circuit power (*i.e.* $211\,[mW]$ for both MQAM and MPSK) and the term R is the transmitting rate computed for each constellation by using the cutoff curves.
- For the MFSK modulation, by considering a non-coherent detection, the well known relation $M = 2T_S B$ [16] allows to derive $T_S = M/2B$, therefore the energy for the transmission will be equal to:

$$E_{infBit} = \frac{(1+\delta) \cdot SNR \cdot N_0 \cdot N_f \cdot G_d}{R} + \frac{P_c \cdot M}{2 \cdot R \cdot B} + \frac{P_{tr} \cdot T_{tr}}{L} \quad (12)$$

  where $\eta = 0.75$ is the typical value for class B or even greater (C, D, or E) power amplifiers [19], $\xi = 1$ according to [18] and $P_c = 165.3\,[mW]$ for general MFSK modulation schemes.

4.6 Cut-off rate curves

In this work, we decided to use the relation between cut-off rate and pre-detection SNR to model the required power of the received signal; this choice is mainly motivated by the fact that the cut-off rate is considered as a meaningful measure of the effective maximum rate for convolutional coding with sequential decoding [16]. These relations can be calculated for MQAM and MPSK by the following formulas [17]:

$$R_0 = 2\log_2(M) - \log_2\left(\sum_{m=1}^{M}\sum_{i=1}^{M} C(x_m, x_i)\right)$$

where $C(x_m, x_i)$ is the Chernoff bound on the pair-wise error probability that for an AWGN channel having a Rician factor of $K = \infty$ we have:

$$C(x_m, x_i) = \exp\left(-\frac{1}{4}|d_{mi}|^2\right)$$

with $|d_{mi}|^2 = |x_m - x_i|^2/N_0$ and x_j is the j^{th} signal.

For noncoherent MFSK we have [16]:

$$R_0 = -\frac{1}{T_s} \cdot \log_2\left\{\frac{1}{M} + \left(1 - \frac{1}{M}\right) \cdot \exp\left(-\frac{\alpha^2}{2}\right)\left[\int_0^\infty x \cdot \exp\left(-\frac{x^2}{2}\right) \cdot \sqrt{I_0(\alpha x)}\, dx\right]^2\right\} \quad (13)$$

where $\alpha^2/2 = SNR$ and $I_0(\alpha r)$ is the modified bessel function of the first kind. They are shown in Fig. 4.

5 The Optimization Model

In this section, we give the mathematical formulation of the problem under study, as an integer nonlinear programming model. It is assumed that the field is represented by a two-dimensional grid. The parameters used for the formulation are the following: h: the grid height; w: the grid width; d_s: the discretization step; $sink$: a particular node that is located in

1. $\xi = 3 \cdot \frac{(\sqrt{M}-1)}{\sqrt{M}+1}$ for square constellations whereas M is the constellation size, while it assumes a value among those shown in Tab. 1 of the work [18] for cross-shaped constellations.

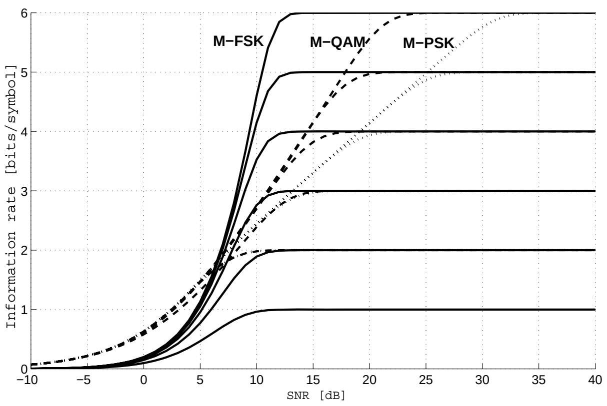


Fig. 4. Capacities and cutoff rates of MQAM, MPSK, and MFSK in AWGN channel as a function of predetection SNR. Each curve represents a different constellation size. The curves $1 \leq \log_2 M \leq 6$ for M-FSK, and $2 \leq \log_2 M \leq 6$ for M-QAM and M-PSK are shown, where M is the constellation size.

a defined a-priori position; n: the total number of available nodes, including the $sink$; r: the sensing radius; tx_{radius}: the transmission radius; M: a large positive number.

The variables of the proposed model are:

- (x_k, y_k), $k = 1, \ldots, n$ the Cartesian coordinates that indicate the location of the node k in the field;
- ϕ_{ijk}, $i = 1, \ldots, \lceil h/d_s \rceil$, $j = 1, \ldots, \lceil w/d_s \rceil$, $k = 1, \ldots, n$ a binary variable that takes the value one if the location (i, j) is covered by node k, and zero otherwise;
- ϕ^+_{ijk}, ϕ^-_{ijk}, $i = 1, \ldots, \lceil h/d_s \rceil$, $j = 1, \ldots, \lceil w/d_s \rceil$, $k = 1, \ldots, n$ are support variables;
- δ_{ij}, $i = 1, \ldots, \lceil h/d_s \rceil$, $j = 1, \ldots, \lceil w/d_s \rceil$, a binary variable that takes the value one if the location (i, j) is covered by at least one node, and zero otherwise;
- γ_{ij}, $i = 1, \ldots, n$, $j = 1, \ldots, n$, a binary variable that takes the value one if the node i is linked to node j, and zero otherwise;
- x_{ij}, $i = 1, \ldots, \lceil h/d_s \rceil$, $j = 1, \ldots, \lceil w/d_s \rceil$, an integer flow variable that is used to represent the paths from each node to the $sink$;
- ψ^+_k, and ψ^-_k $k = 1, \ldots, n$ variables used to represent a relaxed version of the flow conservation constraints.

The considered problem can be mathematically stated as follows:

$$max \quad \alpha \times \left(\frac{\sum_{i=1}^{\lceil h/d_s \rceil} \sum_{j=1}^{\lceil w/d_s \rceil} \delta_{ij}}{h/d_s \times w/d_s}\right) - \beta \times \frac{\sum_{k=1}^{n} \psi^+_k + \psi^-_k}{2 * (n-1)} \tag{14}$$

$$r - |i - x_k| \geq M\ (\phi^+_{ijk} - 1), \ \ \forall i, j \ and \ k = 1, \ldots, n-1 \tag{15}$$

$$r - |j - y_k| \geq M\ (\phi^-_{ijk} - 1), \ \ \forall i, j \ and \ k = 1, \ldots, n-1 \tag{16}$$

$$2 * \phi_{ijk} \leq \phi^+_{ijk} + \phi^-_{ijk} \ , \ \ \forall i, j \ and \ k = 1, \ldots, n-1 \tag{17}$$

$$\delta_{ij} \leq \sum_{k=1}^{n-1} \phi_{ijk}, \quad \forall i, j \tag{18}$$

$$M\ \delta_{ij} \geq \sum_{k=1}^{n-1} \phi_{ijk}, \quad \forall i, j \tag{19}$$

$$|x_i - x_j| - tx_{radius} \leq M\ (1 - \gamma^+_{ij}), \ \ \forall i, j = 1, \ldots, n \tag{20}$$

$$|y_i - y_j| - tx_{radius} \leq M\ (1 - \gamma^-_{ij}), \ \ \forall i, j = 1, \ldots, n \tag{21}$$

$$2 * \gamma_{ij} \leq \gamma^+_{ij} + \gamma^-_{ij} \ , \ \ \forall i, j = 1, \ldots, n \tag{22}$$

$$x_{ij} + x_{ji} \leq (n-1) * \gamma_{ij}, \ \ \forall i, j = 1, \ldots, n \tag{23}$$

$$\sum_{j=1, j \neq i}^{n} x_{ij} - \sum_{j=1, j \neq i}^{n} x_{ji} + \psi^+_i - \psi^-_i = 1, \ \ \forall i = 1, \ldots, n-1 \tag{24}$$

$$\sum_{j=1, j \neq i}^{n} x_{sink\ j} - \sum_{j=1, j \neq i}^{n} x_{j\ sink} + \psi^+_{sink} - \psi^-_{sink} = n-1 \tag{25}$$

$$0 \leq x_k \leq \lceil h/d_s \rceil\,, \quad 0 \leq y_k \leq \lceil w/d_s \rceil\,, \quad \forall k \tag{26}$$

$$x_k, \ \ y_k \ \ integer, \quad \forall k \tag{27}$$

$$\phi_{ijk}, \phi^+_{ijk}, \phi^-_{ijk} \quad binary, \quad \forall i, j, k \tag{28}$$

$$\delta_{ij} \quad binary, \quad \forall i, j \tag{29}$$

$$\gamma_{ij}, \gamma^+_{ij}, \gamma^-_{ij} \quad binary, \quad \forall i, j = 1, \ldots, n \tag{30}$$

$$x_{ij} \geq 0, \ integer \ \ \forall i, j = 1, \ldots, n \tag{31}$$

$$\psi^+_i, \psi^-_i \geq 0, \ integer \ \ \forall i = 1, \ldots, n \tag{32}$$

The objective function in (14) maximizes the number of locations covered by at least one node and the number of nodes that reach the $sink$. Conditions (15) - (17) state that if the distance between the node k and the location (i, j) is lower than or equal to the sensing radius r than the variable ϕ_{ijk} takes the value one, otherwise it is set to zero. Constraints (18) and (19) are logical constraints and ensure that the indicator variable δ_{ij} takes on a value of one if the location (i, j) is covered by at least one node and zero otherwise. Conditions (20) - (22) state that if the distance between the node j and the node j is lower than or equal to the tx_{radius} than the variable γ_{ij} takes the value one, otherwise it is set to zero. Constraints (23) ensure that a flow can be sent from node i to node j only if a link between the two nodes exists.

Constraints (24) and (25) represent a relaxed version of the flow conservation constraints, where the variables ψ_i^+ and ψ_i^- give a measure of the violation of these constraints.

Finally, conditions (26)-(32) represent the variable domain constraints.

The mathematical formulation reported above is an integer nonlinear programming model, where the nonlinearity is confined to the constraints (15) - (16) and (20) - (21).

To eliminate the terms with the absolute value, we introduce the additional constraints reported below:

$$d_{x_{ik}} \geq i - x_k \ \ \forall i, k \tag{33}$$

$$d_{x_{ik}} \geq -i + x_k \ \ \forall i, k \tag{34}$$

$$d_{y_{jk}} \geq j - y_k \ \ \forall j, k \tag{35}$$

$$d_{y_{jk}} \geq -j + y_k \ \ \forall j, k \tag{36}$$

$$d_{x_i x_j} \geq x_i - x_j \ \ \forall i, j = 1, \ldots, n \tag{37}$$

$$d_{x_i x_j} \geq -x_i + x_k \ \ \forall i, j = 1, \ldots, n \tag{38}$$

$$d_{y_i y_j} \geq y_i - y_j \ \ \forall i, j = 1, \ldots, n \tag{39}$$

$$d_{y_i y_j} \geq -y_i + y_j \ \ \forall i, j = 1, \ldots, n \tag{40}$$

Thus, constraints (15) - (16) and (20) - (21) are replaced by the following conditions:

$$r - d_{x_{ik}} \geq M\ (\phi_{ijk}^{+} - 1), \ \ \forall i, j, k \tag{41}$$

$$r - d_{y_{jk}} \geq M\ (\phi_{ijk}^{-} - 1), \ \ \forall i, j, k \tag{42}$$

$$d_{x_i x_j} - tx_{radius} \leq M\ (1 - \gamma_{ij}^{+}), \ \ \forall i, j = 1, \ldots, n \tag{43}$$

$$d_{y_i y_j} - tx_{radius} \leq M\ (1 - \gamma_{ij}^{-}), \ \ \forall i, j = 1, \ldots, n \tag{44}$$

6 Validations, Simulations and Results

The proposed *Neural/Genetic* algorithm is evaluated by simulations using FREVO[2], an open source framework for evolutionary design. We took into account a 40×40 cells field, where 64 nodes are placed in a random way according to an uniform distribution. We considered one cell and one time step as discrete units of space and time, respectively. Also the sensing radius of the nodes is $r = 2\ [cells]$ and it expresses the number of cells that nodes are able to cover in each of the four main direction (north, south, east and west). For the neural network, we use 9 input neurons, 2 hidden neurons and 2 output neurons. For the genetic algorithm, we use 300 chromosomes and 100 generations. All the results have been averaged over 10 different runs to respect a confidence interval of 95%.

In order to conduct a quite realistic analysis on the energy consumption, we chose to set transmitting power ($12\ dBm$) and receiver sensitivity ($-80\ dBm$) of our devices by referring to an off-the-shelf Bluetooth module made by *Roving Networks* [20]. Table 2 summarizes all the other simulation parameters used.

TABLE 2
Values of the relevant parameters used for the simulations

Device Parameters	
Power spent in *transient* mode (P_{tr})	100 $[mW]$
Time spent in *transient* mode (T_{tr})	5 $[\mu s]$
Wavelength (λ)	0.125 $[m]$
Information bits (L)	1000 $[bits]$
Receiver noise figure (N_f)	10
Bandwidth (B)	10 $[kHz]$
Scenario Parameters	
Path Loss Exponent (γ)	3.8
Critical distance (d_0)	1 $[m]$
PSD of the noise ($N_0/2$)	$10^{-15}/2\ [W/Hz]$
Bit Error Rate ($BER_{threshold}$)	10^{-3}
Maximum number of time steps	100
Genetic Algorithm Parameters	
% of elite selection (e)	15%
% of mutation (mu)	45%
% of crossover (c)	30%
% of created offsprings (off_c)	5%
% of selecting an offspring (off_s)	5%

6.1 Validation of the Optimizazion Model

This first simulation campaign aims at validating the optimization model formulated in section 5. The presented results have been achieved by using LINGO 9.0[3] for the mathematical model and they have been averaged over 100 runs with a confidence interval of 95%. For this simulation campaign we use a simple scenario with a 6×6 cells field, where $\{3; 4; 5\}$ nodes are placed in a random way according to an uniform distribution. Also the sensing radius of the nodes is $r = 1\ [cell]$ and the transmission radius is $tx_{radius} = 1\ [cell]$. The discretization step is $d_s = 1$ and the large positive number M is equal to 1000. Fig. 5 shows that the behaviour of the algorithm proposed is very close to the centralized optimum obtained through the mathematical model for each value of *alpha/beta* within the Fitness function. In order to assess the

2. http://www.frevotool.tk

3. http://www.lindo.com

behaviour of the proposed optimization model, test problems, characterized by a small field size and a limited number of nodes, have been considered. This choice is motivated by the fact that the intrinsic complexity of the model allows to solve, in a reasonable amount of time, only small size instances. For this reason, once we validated the satisfying accuracy of the optimization model respect to the proposed heuristic scheme, we conducted a more intensive simulation campaign to explore several configuration parameters with an higher number of nodes within a wider area.

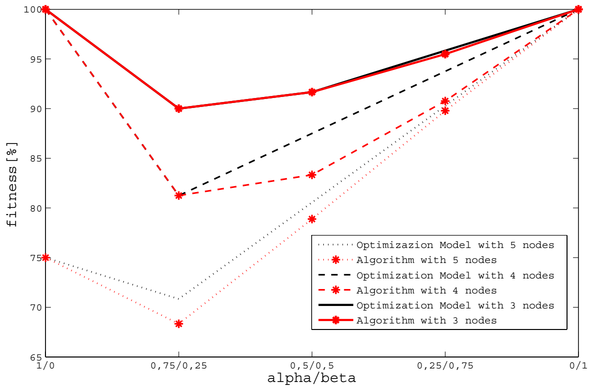


Fig. 5. Validation of the Neural/Genetic Algorithm: Heuristic vs. Optimization model.

6.2 Fixed nodes analysis supporting SDR

In this section we show the results obtained throughout the support of SDR capabilities; in this context the communication devices are all fixed but they can autonomously decide to use one of three different modulation schemes (MFSK, MPSK, MQAM) with three different symbol levels M (4, 8, 16) thus the set of possible choices is extended to nine. However, since the mobility support is out of the scope of this first reference simulation scenario, the Neural/Genetic algorithm described in section 4 cannot be executed every new generation and the result, in terms of more suitable modulation schemes, in agreement with the desired QoS, is always the same representing the reference benchmark point for the next analysis in which the mobility of the nodes allows to achieve better performances.

Figure 6, obtained throughout the implemented simulation framework, shows a clear example of a communication scenario in which the nodes are fixed but the use of SDR capabilities allows them to achieve different results in terms of $\text{QoS}_{connectivity}$. In particular, in figure 6.(a) the circles representing the nodes, are coloured in different ways according to the different supported modulation schemes (i.e., yellow for FSK, cyan for QAM and magenta for PSK). The square around the circle represents the communication ability of each node (i.e., blue if they can reach the sink node, red if they can communicate between each others without reaching the sink node). On the other site, the nodes displayed in figure 6.(b) are all coloured in blue because they can choose to use all the different modulation schemes according to the new features provided by the SDR technology. Thus, they can communicate with more neighbours respect to the previous scenario in order to reach the sink node by increasing the performance in terms of $\text{QoS}_{connectivity}$. On the contrary, the $Coverage$ cannot take advantage from the SDR technology due to the lack of mobility support.

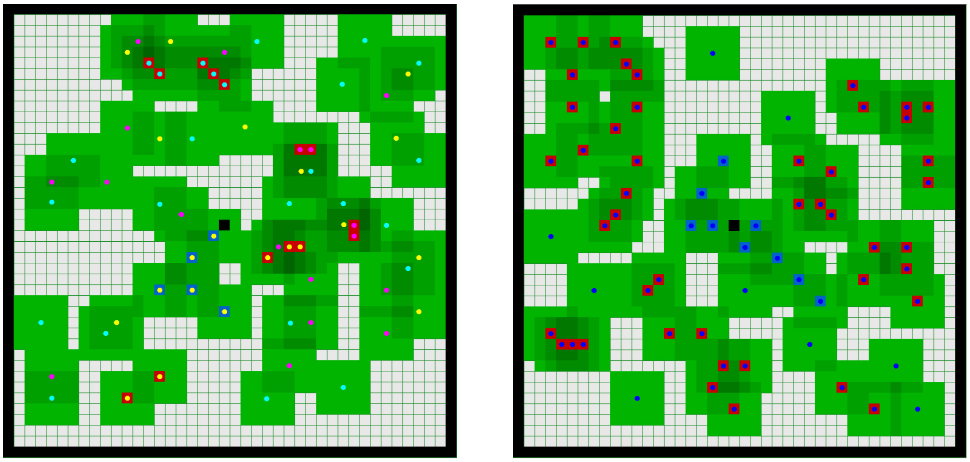
Table 3 summarizes the obtained results over 1000 simulation runs, also specifying the percentage of nodes that have chosen any specific modulation scheme and the average energy consumption for the transmission. It is worth to note that in the simulated scenario few modulation schemes such as 4-8-PSK have never been chosen due to the worst performance in terms of BER and to the higher energy consumption.

TABLE 3
Fixed nodes analysis supporting or not supporting SDR capabilities

Output Parameters	Without SDR	With SDR
$Coverage$	61.57%	61.47%
$\text{QoS}_{connectivity}$	2.03%	12.20%
Energy per Information Bit	$2.4 \cdot 10^{-5}$ $[J]$	$2.75 \cdot 10^{-5}$ $[J]$
Nodes choosing 4-FSK	12.59%	0%
Nodes choosing 8-FSK	28.34%	38.57%
Nodes choosing 16-FSK	34.82%	43.92%
Nodes choosing 4-PSK	0%	0%
Nodes choosing 8-PSK	0%	0%
Nodes choosing 16-PSK	10.80%	10.94%
Nodes choosing 4-QAM	0%	6.57%
Nodes choosing 8-QAM	0%	0%
Nodes choosing 16-QAM	13.45%	0%

6.3 Mobile nodes analysis supporting SDR

In this section we show how controlled mobility can be efficiently exploited to reach better configurations both in terms of $Coverage$ and $QoS_{connectivity}$. In Figures 7 we show results obtained when all nodes are equipped with motion capabilities but they are not able to select, in a dynamic fashion, the most suitable modulation. Specifically, all nodes will support only a specific modulation scheme in a random way, by keeping the percentage of nodes that choose a certain modulation equal for all the modulation schemes. In this specific case, the 33.33% of nodes will support FSK or QAM or PSK modulation. Of course, in order to obtain reliable results we averaged them complying a confidential interval of 95%. In this scenario, all nodes will move in a distributed fashion towards novel positions computed through the neural network



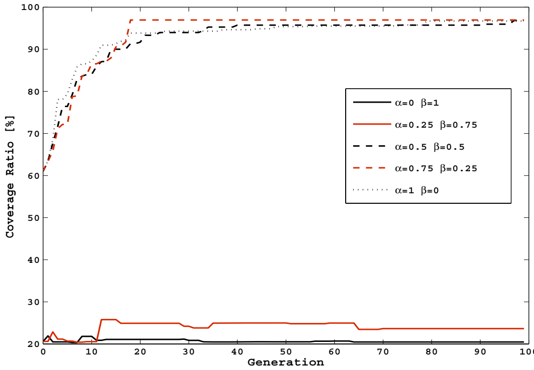
(a) (b)

Fig. 6. Fixed nodes communication scenario: (a) No mobility without SDR, (b) No mobility with SDR.

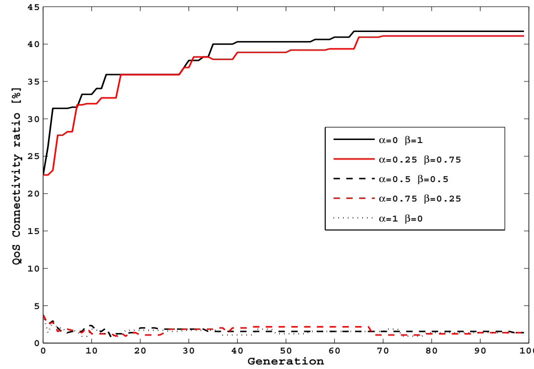
by considering a genetic approach during the training phase as explained in Section 4. It is worth to notice that in the configuration where nodes are not able to move, $Coverage$ cannot be improved and nodes are only allowed to choose a better modulation in order to improve $QoS_{connectivity}$. When nodes are able to move, better configurations in terms of both $Coverage$ and $QoS_{connectivity}$ are obtained. For α values ranging from 0.5 to 1, after 20 Generations the nodes are able to reach a percentage of coverage higher than 90%. Concerning the $QoS_{connectivity}$ index, it is increased from 12.2% to 35% after ≈ 35 Generations by tuning the connectivity parameter (β) with higher values, 0.75 and 1. Unfortunately, if we observe the curves related to $Coverage$ and $QoS_{connectivity}$ in a cross-way, we notice as controlled mobility is a valid tool to improve performance of the system, but coverage and connectivity are opposite goals, and then controlled mobility is able to generate configuration that "answer" in an effective way to the setting of α and β, but it is not able to handle the opposition of those two QoS requirements. In fact, in Figure 7 (a), when the value of α is chosen equal to 0.25, the network is not able to reach a degree of coverage higher than $\approx 24\%$, and this is the case (see Figure 7 (b)) where the connectivity value reaches $\approx 42\%$. By considering an additional freedom degree consisting into the possibility to set the most suitable modulation, the overall performance of the system are improved as shown in Figure 8 (a) and (b). A strange effect of the dynamic modulation setting occurs when α and β are both set equal to 0.5. In this case (see Figure 8 (a)), coverage reached is smaller than in the previous case, but it is worth to analyze this behavior in combination with the connectivity value. In fact, in Figure 8 (b), in correspondence of the same α and β values, we are able to obtain a connectivity degree higher than 93% after very few Generations. On the other hand, the system gives an answer matching the interest we express with the α value, since we set α equal to 0.5. When the α value is higher than 0.5, the system takes properly into account this setting and the coverage increases. From this analysis, we can argue that, by considering in a similar way the importance of both α and β parameters, the system will behave in a very effective fashion guaranteeing a very high level of $QoS_{connectivity}$ and a good degree of $Coverage$. These results are also confirmed by the *Fitness* curves shown in Figures 7 (c) and 8 (c) respectively. In fact, we can observe as *Fitness* improves by reaching very high values after a few number of generations when the weight associated with connectivity is the highest possible ($\alpha = 0$ and $\beta = 1$). In respect of the case in which nodes are only equipped with motion capabilities, SDR mobile nodes are able to react to the connectivity requests of the networks. Moreover, in all the studied cases we can notice an improvement of the *Fitness* except when coverage is considered as a kind of high priority (*i.e.* $\alpha = 0.75$ or $\alpha = 1$) making the *Fitness* trend similar to the case with no-SDR mobile nodes. As main conclusion of this simulation campaign, we can argue that, by correctly tuning the α and β weights of the *Fitness* function, the wireless network consisting of self-configuring SDR devices can dynamically react in order to face different communication scenarios by favoring, from time to time, the $Coverage$, the $QoS_{connectivity}$ or both.

6.4 Mobile nodes analysis with variable amount of SDR nodes

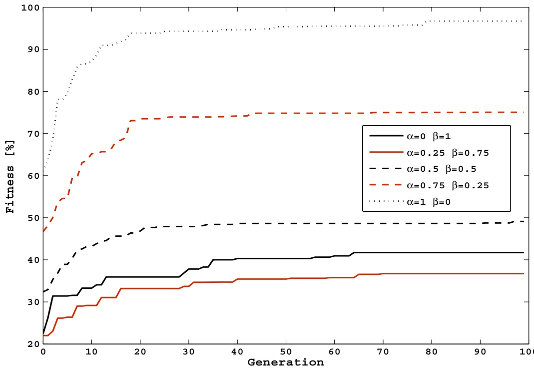
In this section we investigate the impact of the amount of SDR nodes on the overall network performances because, as detailed in section 3 and in table 1, the SDR nodes are still quite expensive devices; thus it is convenient to reduce their number as much as possible. We tested the system with mobile nodes by choosing the same value for the parameters of the



(a) Coverage$_{ratio}$

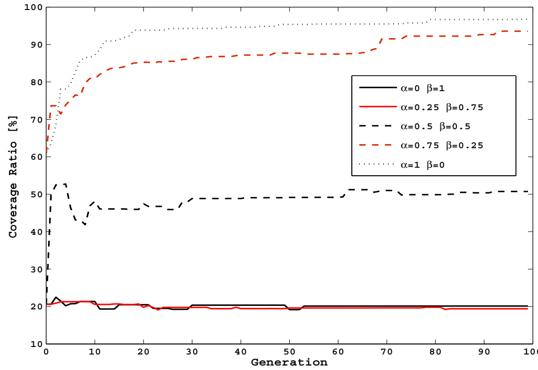


(b) QOS$_{connectivity_ratio}$

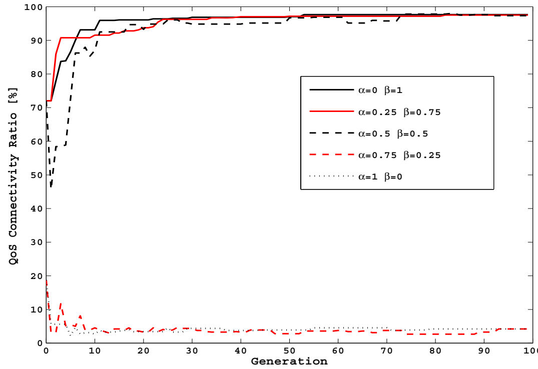


(c) Fitness

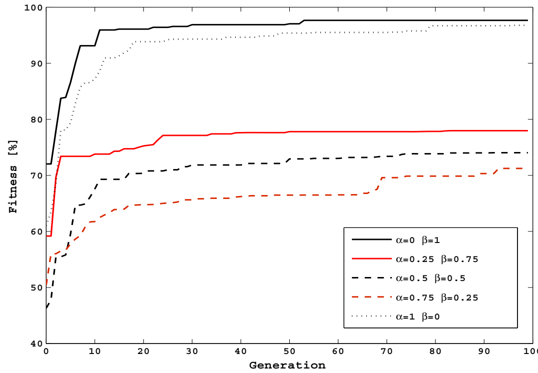
Fig. 7. Neural/Genetic algorithm supporting mobility without SDR capabilities: (a) Coverage, (b) QoS$_{connectivity}$, (c) Fitness



(a) Coverage$_{ratio}$



(b) QOS$_{connectivity_ratio}$



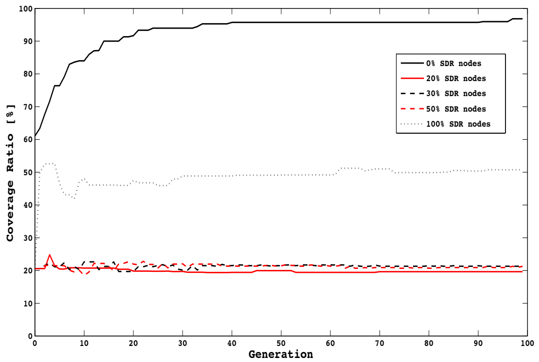
(c) Fitness

Fig. 8. Neural/Genetic algorithm supporting mobility and SDR capabilities: (a) Coverage, (b) QoS$_{connectivity}$, (c) Fitness

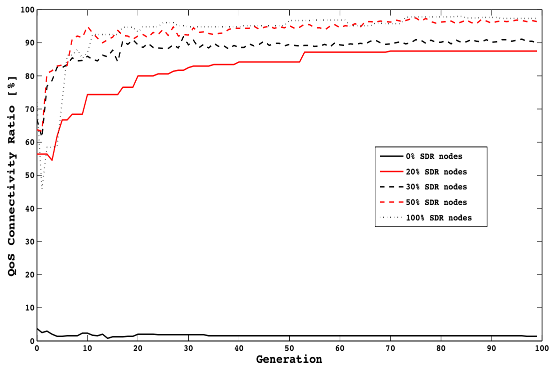
Fitness function (i.e. $\alpha = \beta = 0.5$) and varying the percentage of SDR nodes (i.e. $0\%; 20\%; 30\%; 50\%; 100\%$). The obtained results, shown in figure 9, demonstrate that even using a small amount of SDR nodes, it is possible to achieves good performances in terms of $QoS_{connectivity}$ (figure 9.b) but the $Coverage$ turns out to be considerably reduced due to the fact that the nodes equipped with SDR capabilities work as attractors for the nodes without those features by greatly reducing the possibility to expand to cover larger areas.

6.5 Varying the percentange of mobile nodes

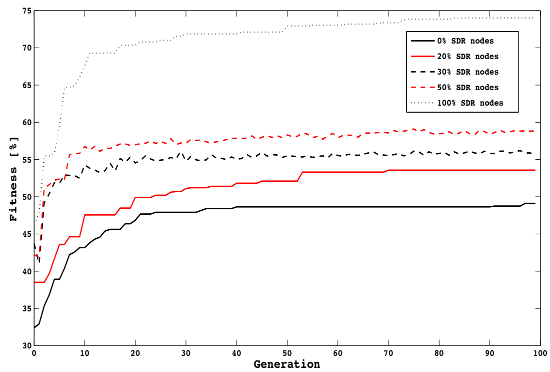
In this scenario we investigate the impact of high number of mobile SDR nodes on the overall network performances. This analysis is mainly motivated by the fact that the mobility capability has a quite expensive cost and the SDR equipment is still a bit expensive at the present day. According to these remarks, it makes sense to test how these capabilities impact on the performance of the network, both in terms of coverage and connectivity toward the sink; thus we consider only a portion of nodes equipped with SDR capabilities by varying the number of nodes



(a) Coverage_{ratio}



(b) $\text{QOS}_{connectivity\_ratio}$



(c) Fitness

Fig. 9. Neural/Genetic algorithm supporting mobility and percentage of nodes with SDR capabilities: (a) Coverage_{ratio}, (b) $\text{QOS}_{connectivity\_ratio}$, (c) Fitness

able to move toward "better" positions. In this way, we aim at dimensioning the right number of mobile nodes in order to save money without excessively reduce the network performances. With this goal in mind, we decided to test a network scenario in which only half of the nodes are provided with SDR functionalities and, among the standard nodes, a variable percentage are equipped with mobile capabilities (i.e. $40\%; 60\%; 80\%; 100\%$). Just to give a numerical example, let us consider 64 nodes in the network field, 32 among them are equipped with SDR capabilities and are static whilst the number of mobile nodes, without SDR capabilities, varies as follows: 12, 19, 25 and 32.

The obtained results are shown in figure 10. As already explained, by using a certain percentage of SDR nodes it is possible to improve the network performances in terms of connectivity but at the expense of coverage; on the other side, by considering a more realistic network scenario in which not all the nodes can move, the effect of attraction mechanism, due to the SDR nodes, decreases thereby improving the performance in terms of coverage. However, if the percentage of standard mobile nodes is lower than 80%, we experienced a bad connection management toward the sink node; i.e. to reach the more isolated fixed nodes, the SDR nodes prefer to ensure optimal coverage rather than communicate with the sink.

As main conclusion of this simulation campaign, we can argue that it is possible to decouple the effects due to both SDR and mobility features; in fact, in a mixed scenario in which only a portion of fixed nodes are equipped with SDR capabilities, a good $QoS_{connectivity}$ level can be guaranteed by increasing the number of mobile standard nodes.

7 Conclusions

In this paper we considered SDR mobile nodes able to move towards most suitable positions and to select the best modulation scheme in order to both improve the coverage within a specific area and the connectivity to a sink node. All nodes run an algorithm based on a totally distributed Neural/Genetic approach by using only local information. As main conclusion of the different simulation campaigns we can argue that the proposed strategy can handle the two opposite requirements, represented by the coverage and the connectivity, in a dynamic fashion by wisely tuning the fitness function parameters; moreover, we demonstrated that, quite similar performances, can be achieved also using a reduced amount of devices equipped with expensive SDR and mobility features by making the proposed solution more attractive from an economic point of view. As future work we would like to test our strategy by implementing a proof of concept on real devices.

Acknowledgment

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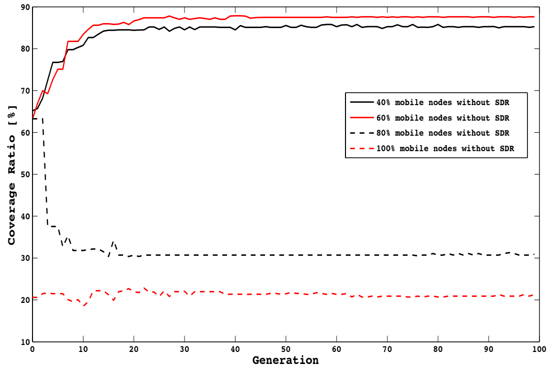
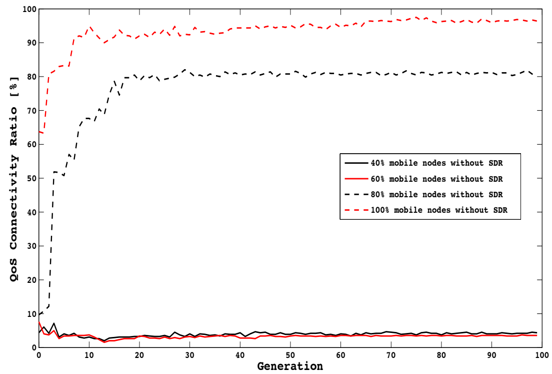
References

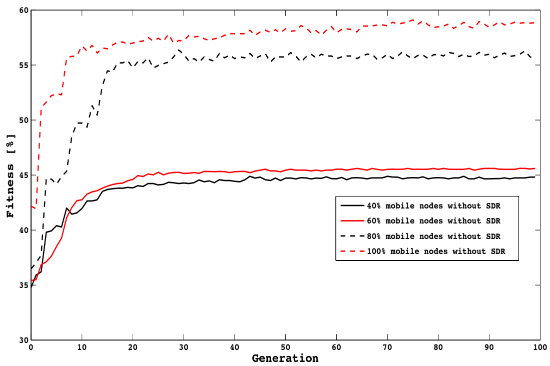
[1] G. Aloi, L. Bedogni, M. Di Felice, V. Loscrì, A. Molinaro, E. Natalizio, P. Pace, G. Ruggeri, A. Trotta. N. R. Zema, "STEM-NET: An Evolutionary Network Architecture for Smart and Sustainable Cities", *Transactions on Emerging Telecommunication Technologies*, Special Issues on Smart Cities, Vol. 25, Issue 1, pages 2140, January 2014.



(a) Coverage_{ratio}



(b) $\text{QOS}_{connectivity\_ratio}$



(c) Fitness

Fig. 10. Neural/Genetic algorithm supporting SDR capabilities and percentage of mobile nodes: (a) Coverage_{ratio}, (b) $\text{QOS}_{connectivity\_ratio}$, (c) Fitness

[2] M. Di Felice, L. Bedogni, A. Trotta, L. Bononi, F. Panzieri, G. Ruggeri, G. Aloi, V. Loscrì, P. Pace, "Smartphones Like Stem Cells: Cooperation and Evolution for Emergency Communication in Post-Disaster Scenarios", in Proceedings of IEEE International Black Sea Conference on Communications and Networking (BlackSeaCom 2013), July 3-5, 2013, Batumi, Georgia.
[3] C. Blümm, C. Heller, R. Weigel, "SDR OFDM Waveform Design for a UGV/UAV Communication Scenario", *Journal of Signal Processing Systems*, Vol. 69, Issue 1, pp 11-21, October 2012.
[4] V. Pejovic and E. M. Belding, "WhiteRate: A Context-Aware Approach to Wireless Rate Adaptation", *IEEE Transactions on Mobile Computing*, Volume 13, Issue 4, April 2014, pp. 921-934.
[5] B. B. Godbole and D. S. Aldar, "Performance Improvement by Changing Modulation Methods for Software Defined Radios", *International Journal of Advanced Computer Science and Applications*, 1(6), Dec. 2010.
[6] P. Pace and G. Aloi, "Disaster monitoring and mitigation using aerospace technologies and integrated telecommunication networks", *IEEE Aerospace and Electronic Systems Magazine*, 23(4), April 2008.
[7] V. Loscrì, P. Pace, R. Surace, "Multi-objective evolving neural network supporting SDR modulations management" Proceedings of 24th IEEE Personal Indoor Mobile and Radio Communications (PIMRC), 8-11 September, London-UK, 2013.
[8] I. Oka and M.P.C. Fossorier, "A General Orthogonal Modulation Model for Software Radio", *IEEE Transactions on Communications*, vol. 54, No.1, Jan. 2006, pp. 7-12.
[9] E. Marpanaji *et al.*, "Experimental Study of DQPSK Modulation on SDR Platform", *ITB Journal of Information and Communication Technology*, vol. 1, No.2, 2007, pp. 84-98.
[10] GNU Radio. http://gnuradio.org. - Accessed on March. 2, 2013.
[11] Ettus Research LLC. http://www.ettus.com - Accessed on March. 2, 2013.
[12] T. R. Mück and A. A. Fröhlich, "HYRA: A Software-defined Radio Architecture for Wireless Embedded Systems", 10th International Conference on Networks (ICN), January, 23-28, 2011.
[13] C. Costanzo, V. Loscrí, E. Natalizio, T. Razafindralambo, "Nodes self-deployment for coverage maximization in mobile robot networks using an evolving neural network", *Computer Communications*, 35(9), 2012.
[14] G. Molina and E. Alba and E. Talbi, "Optimal Sensor Network Layout Using Multi-Objective Metaheuristics", *Journal of Universal Computer Science*, n 15, pp 2549-2565, vol. 14, 2008.
[15] R. Surace, V. Loscrí, and E. Natalizio, "On the impact of the propagation environment on controlled mobility algorithms", in International Workshop on Mobility and Communication for Cooperation and Coordination (MC3) at IEEE ICNC 2012, pp. 62-66, 2012.
[16] S. Butman, B. Levitt, I. Bar-David, R. Lyon and M. Klass, "Design Criteria for Noncoherent Gaussian Channels with MFSK Signaling and Coding", *IEEE Transactions on Communications*, vol. 24, No. 10, 1976, pp. 1078-1088.
[17] L. Hanzo, S. Ng, T. Keller and W. Webb, "Quadrature Amplitude Modulation: From Basics to Adaptive Trellis-Coded, Turbo-Equalised and Space-Time Coded OFDM, CDMA and MC-CDMA Systems", John Wiley, 2004.
[18] F.M. Costa and H. Ochiai, "A comparison of modulations for energy optimization in wireless sensor network links", IEEE Global Telecommunications Conference (GLOBECOM), pp 1-5, December 2010.
[19] S. Cui, A.J. Goldsmith and A. Bahai, "Energy-constrained modulation optimization", *IEEE Transactions on Wireless Communications*, 4(5):2349-2360, September 2005.
[20] Roving Networks wireless for less WiFly GX 802.11G Super Module: RN-121, RN-122, RN-123, RN-125. http://www.rovingnetworks.com
[21] A. Goldsmith, "Wireless Communications", Cambridge University Press, August 2005.
[22] M. Michal, "A survey of Multi-Objective deployment in Wireless Sensor Networks", *Journal of Telecommunications and Information Technology*, vol. 2010, issue 3, pp. 36-41, 2010.
[23] S. R. Goyal, "A Survey on deployment Methods in Wireless Sensor Networks", *International Journal of Advanced Research in Computer Science and Software Engineering*, vol. 3, issue 7, July 2013.
[24] L. P. Damuut and D. Gu, "Survey of Deterministic Vs Non-Deterministic Node Placement Schemes in WSNs", in the sixth International Conference on Sensor Technologies and Applications, SENSORCOMM 2012.
[25] P. Stuckmann and R. Zimmermann, "Toward ubiquitous and unlimited-capacity communication networks: European research in Framework Programme 7", *IEEE Communications Magazine*, vol. 45, Issue 5, May, 2007.
[26] B. B. Godbole and D. S. Aldar, "Performance Improvement by Changing Modulation Methods for Software Defined Radios", *International Journal of Advanced Computer Science and Applications (IJACSA)*, vol. 1, No 6, December 2010.
[27] R. R. Bhambare and R. D. Raut, "A Survey on Digital Modulation Techniques for Software Defined Radio Applications", *International Journal of Computer Networks and Wireless Communications (IJCNWC)*, ISSN: 2250-3501, vol. 3, No 3, June 2013.